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Aircraft Trajectory Tracking and Prediction

Final Report

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13. ABSTRACT *(Maximum 200 words)*

Regression modelling of trajectory measurement data was examined as a means for improving the performance of aircraft trajectory tracking and prediction. Regression models were used for adaptively removing measurement noise from trajectory observations and extrapolating trajectory measurements. A comparative study was done between three models of aircraft dynamics used in an extended Kalman filter: a strictly translational model, an attitude/translation model, and an attitude/translation model that uses vehicle specific inertial characteristics. Adaptive regression models were used for measurement accuracy enhancement. Comparisons were also made between errors resulting from position and attitude predictions using Runge-Kutta integration and extrapolated regression models.

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Summary

Regression modelling of trajectory measurement data was examined as a means for improving the performance of aircraft trajectory tracking and prediction. Regression models were used for adaptively removing measurement noise from trajectory observations and extrapolating trajectory measurements. A comparative study was done between three models of aircraft dynamics used in an extended Kalman filter: a strictly translational model, an attitude/translation model, and an attitude/translation model that uses vehicle specific inertial characteristics. Adaptive regression models were used for measurement accuracy enhancement. Comparisons were also made between errors resulting from position and attitude predictions using Runge-Kutta integration and extrapolated regression models.

A unique aspect of this study is the use of actual trajectory data. The study was conducted using actual position and attitude trajectory data for F-14A aircraft acquired during training flights. The data is supplied through the Navy's TACTS (Tactical Aircrew Training System) at Cherry Point Marine Corps Air Station.

Overall, the use of attitude information has been confirmed as a means for improving tracking and predictive performance. Regression modelling in both preconditioning measurement data and extrapolating artificial measurements has been demonstrated to be a powerful tool for improving the performance of advanced tracking and prediction techniques.

Acknowledgements

The authors would like to thank the sources of data and advice that were critical in performing this work. Bruce J. Pippett, Loral Aerospace, Edward McMullen, Cherry Point MCAS and T. Daniel Blair, Naval Air Systems Command, were responsible for providing the TACTS trajectory data used to test the tracking algorithms described in this report. Marge Draper-Donley, Cedric Walker and Thomas Lawrence, Naval Air Systems Command, were responsible for providing the vehicle specific characteristics used to implement certain trackers.

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Introduction

This report describes research in the use of regression models of trajectory measurement data for improving the performance of aircraft trajectory tracking and prediction algorithms. Regression models were used to adaptively precondition or remove measurement noise from trajectory observations. Regression models were also considered for extrapolating trajectory measurements when a prediction of aircraft position is required. The regression modelling approach was adopted as a means of better estimating the underlying dynamics of the aircraft as observed through position and attitude measurements.

A comparative study was done between three models of aircraft dynamics used in an extended Kalman filter: a strictly translational or center of gravity model, a model that incorporates both aircraft attitude and translation, and an attitude/translation model that uses vehicle specific inertial characteristics. Comparisons were made between the tracking and prediction errors for the three models using measurement data directly and using data that was preconditioned by adaptive regression models. Comparisons were also made between errors resulting from position and attitude predictions using Runge-Kutta integration and regression models.

Numerous investigators have shown the importance of attitude data in the tracking and prediction of aircraft trajectory [1,2,3,27,30,31]. This work builds upon the type of tracker proposed by Andrisani [1,2,3]. This approach exploits the relationship between vehicle attitude and acceleration. The previous work applies measurement data directly to the tracker and Runge-Kutta integration to predict the future trajectory. The new approach in this work considers measurement data preconditioned by linear Kalman filters derived from power series regression models that are constantly updated by new measurements. In addition, this approach uses a new means of predicting future trajectories by using the most recent regression model for extrapolating trajectory measurements. The extrapolated measurements are used to continue the operation of the tracker during the prediction interval.

The study was conducted using actual position and attitude trajectory data for F-14A aircraft acquired during training flights. The data is supplied through the Navy's TACTS (Tactical Aircrew Training System) at Cherry Point Marine Corps Air Station. All positional data is collected by ground-based radar and attitude data is collected using on-board gyroscopic instruments. A unique aspect of this study is the use of actual trajectory data. Many prior comparative studies of filter performance have been made using purely simulated data or attitude data estimated from translational data.

Preconditioning Measurement Data

The measurements used in the tracking filters consist of a vector of translational data in polar coordinates and their corresponding derivatives. These are coupled with the aircraft body attitude in terms of Euler angles. The translational information is derived from radar observations. The attitude data is gyroscopically derived on board the aircraft and transmitted to the ground station. In an actual tracking engagement, these angles are assumed to be estimated by an electro-optical image sensing technique. The symbols used for all of the measured parameters are given in Table 1. The important attitude and translational measurement data are summarized in Table 2. All of the measurements are used in measurement equations for the extended Kalman filter. Each measurement has an additive noise term to account for measurement uncertainty. The measurement noise terms are assumed to be Gaussian, white, and statistically independent from the other measurement noises, any process noise and the initial state of the aircraft trajectory.

This study used a new technique for enhancing the effectiveness of tracking and prediction filters. Independent linear Kalman filters for each measured parameter associated with the trajectory were used to "precondition" the observations prior to use in the tracking and prediction filter. Independent parameters such as range, azimuth and elevation as well as roll, pitch and yaw are preconditioned in order to improve the resultant state estimates. The basic concept involves the creation of a regression model (specifically, an nth order power series in time) of the parameter signature over a brief interval. The resulting regression model is differentiated n times. The resulting differential equation is converted into a state model and used to implement a linear Kalman filter for that measurement [17,18,19,20,21]. A flowchart illustrating the regression modelling process is shown in Figure 1. A derivation of the method for converting a power series into a state model is provided in Appendix A.

The regression model is updated for each time step in the discrete measurement process. Statistics for the process noise are extracted from the model derived at each time step. Measurement noise statistics are found by conventional techniques. This approach makes the usual assumptions regarding the statistics of the states and disturbances. It should be noted that the "state" of the measurement that results from this modeling is not identical to the vector consisting of the measurement and its relevant time derivatives. However, a linear transformation can be performed to convert this state into the units of the measurement. This transformation is also extracted from the regression model [17,18,19].

This method is intended to remove noise disturbances from a measurement that has significant dynamics. It has been shown to be effective in improving the quality of measurement signatures in a variety of manufacturing processes [20,21]. The method uses an assumption that a time-varying measurement has dynamics that are describable and applicable to a linear Kalman filter. These dynamics may not be understood from "first principles"; however, they may be described in a terms of a regression model. The regression model derives useful information from the measurement process and helps in estimating the actual measurement.

This approach is not simply a low-pass filtering of the measurement. The regression model for the measurement is selected based on the statistical significance of the terms in the power series. If the measurement process has high-order dynamics, corresponding terms in the regression model will be significant in describing the time signatures (as evaluated by standard t-tests and F-tests). In practice, short intervals of aircraft trajectory measurements such as range can be effectively models by a third-order power series. This is reasonable since the measurement is likely to be describable in terms of velocity, acceleration and jerk.

Figures 2-10 show actual F-14A trajectory measurements over a nine second interval. The actual measurements, noisy measurements and preconditioned estimates are shown. The noisy and preconditioned measurements were both used in the extended Kalman filter estimator for trajectory tracking. These figures illustrate the ability of linear Kalman filters, derived from regression models of noisy data, to effectively estimate the underlying measurements of the aircraft trajectory with significant disturbances.

The adaptively created regression models were also used in the trajectory prediction process. Previous investigations used Runge-Kutta integration of the last tracked state in order to predict future states through the time update cycle in the extended Kalman filter. The regression models derived for preconditioning allow prediction to be performed in a novel way. The last estimated regression model of the measurement is used to extrapolate the measurement throughout the prediction interval. The extrapolated data in the prediction interval is shown at the end of each trajectory measurement shown in Figures 2-10. In the process of testing the various tracking techniques, extrapolations were made every second. The extrapolations shown are for illustrative purposes. These extrapolations or "artificial measurements" are used to continue the operation of the extended Kalman filter during the prediction interval. The state and measurement update cycles of the extended Kalman filter are executed in the identical fashion as they were during the tracking interval.

Models Used for Trajectory Tracking

Three different dynamic models of the aircraft trajectory were used in this investigation. Comparisons were made between these models of aircraft dynamics used in an extended Kalman filter: a strictly translational or center of gravity model, a model that incorporates both aircraft attitude and translation, and an attitude/translation model that uses vehicle specific inertial characteristics. The symbols used in the various trackers are defined in Table 1. The measurement vector of all trackers is given in Table 2. It should be noted that the center of gravity tracker does not use the attitude measurements (roll, pitch and yaw).

The center of gravity tracker used three independent estimators for tracking the translation of the aircraft. These trackers are similar to the acceleration model in other center of gravity methods [8,11,23,25,26,40]. A third order Gauss-Markov model is used to approximate the jerk in each coordinate direction. The center of g avity model is given in Table 3. In the process of implementing the filter it became obvious that the acceleration model was the key to reasonable results. An experimentally selected value for the correlation time τ provided robust performance using virtually conditions and sets of input data.

The attitude translation tracker is taken from the work presented in [1,2,3,5]. Fifteen differential equations are shown in Table 4. Six of these equations describe the rotation of the aircraft, six describe the translation and three equations provide the model used for the acceleration. These equations show the importance of vehicle attitude in modeling translation. Orientation of the aircraft provide valuable insight into the direction and rate of the aircraft velocity.

In order to attempt to recreate the work described in [1], no vehicle-specific inertial constants were used in implementing the attitude/translation model. The mathematical model for the angular acceleration of the aircraft was reduced to simply white noise. The only vehicle specific data used in this case were the lift coefficient, span and mass.

The third model used in this study was the attitude/translation model including that vehicle specific inertial characteristics. The inertial data was supplied by NAVAIR for the specific vehicle under test. This substantially more complete model assumed access to the principal moments of inertia for the aircraft. This is a reasonable scenario in cases, since many potential encounters could take place with aircraft that are well understood in terms of the their mass properties (in fact, some may have been built by US suppliers).

Comparative Studies of Filter Performance

An example was used to perform a comparative study of the three tracking filters (center of gravity (CG), attitude/translation (AT) and attitude/translation with vehicle specific inertia (AT-VSI)). These trackers were tested using both noisy and preconditioned measurement data. The standard deviation of the measurement noises are given in Table 5. Two different approaches to predicting the trajectory of the aircraft were used: (1) Runge-Kutta integration of the state equations and (2) continued operation of the extended Kalman filter using artificial measurements extrapolated from regression models of the various measurements.

All tests were conducted using actual aircraft data collected from the TACTs training system at Cherry Point MCAS. Various training runs of F-14A aircraft were available for testing purposes. The particular trajectory used for this work is illustrated in terms of aircraft position and attitude in Figure 11. A vertical line is projected onto a flat earth (or plane tangent to the earth at the radar station) approximately every second. The triangular symbol gives an indication of aircraft attitude only and is not to scale. A plan view of the trajectory is given Figure 12. It should be noted that some of the radar measurements were at ranges up to 5-7 miles.

A portion of the trajectory shown in Figures 11 and 12 was selected to test the comparative performance of the filters. A 4 g turn to the right while diving was the selected maneuver. The turn had accelerations ranging from 0 to 4 g and velocities close to Mach 0.7. The maximum bank angle was close to 90 degrees. The total duration of the selected trajectory was 9 seconds. This position of the trajectory is illustrated in Figure 13. Each of the measurements of the trajectory was corrupted with realistic Gaussian, white, statistically independent noise with statistics given in Table 5.

The results of the tracking and prediction performance are summarized in Appendix B. Four different intervals of tracking are shown in Tables B1-B4. In each case, the tracking errors and the prediction errors corresponding the tracking interval are summarized. There are separate maximum error measurements shown for x, y and z directions. A maximum Euclidean distance is also given. The arithmetic average and the root mean square (RMS) Euclidean errors for the intervals are also given. It is recognized that other error metrics may be used. However, the Euclidean norm was selected as a convenient way of showing comparative performance.

It should be noted that the error measurements are not necessarily a "ground truth" or absolute indication of tracking or prediction accuracy. The measurements are made at a distance of several miles. Furthermore, the measurements are made on a real aircraft with a radar cross section that varies with attitude. Both of these factors limit the ultimate accuracy of the "actual" measurements from the TACTs data. It is suspected that some type of smoothing is performed on the data when it is recorded on the TACTs debriefing system. The contacts at Loral Aerospace who provided the data did not know any details on the smoothing algorithms or where not at liberty to discuss them.

Appendix B shows a sequence of tables corresponding to tracking intervals of increasing duration and one second prediction intervals. In each case, all filters where run on the same data for comparison purposes.

The center of gravity tracker consistently showed the worst tracking performance in terms of maximum Euclidean tracking error with noisy measurements. This result is consistent with the results reported by a number of investigators [1,2,3,27,30,31] when compared to techniques using attitude as a supplementary measurement. However, when the center of gravity tracker is used on preconditioned measurements, its performance approaches that of the attitude/translation tracker. This observation illustrates the importance of preconditioned measurements. Conclusions regarding the relative importance of preconditioning and using attitude data have to be made with some reservations. The ultimate performance of each approach cannot really be defined since the comparisons are being made with real radar data rather than theoretically exact simulation data. Therefore, there is no ground truth for comparison to the actual position of the aircraft, rather there is only comparisons to the best available radar data.

The two versions of the attitude/translation tracker has virtual identical tracking performance. The use of vehicle specific inertia had no significant effect on the performance of the tracker. This result further confirms the conclusions in [1] that the angular rate terms in the state model may be effectively represented as white noise. The most important aspect of this observation is that detailed vehicle specific data is not needed for effective tracking. This is especially beneficial since such data may not be available in a combat scenario.

The results for predicting the trajectory of the aircraft over a one second interval showed the importance of the regression techniques in both preconditioning the data and deriving artificial measurements. Prediction was performed using noisy data with Runge-Kutta integration of the state equations, preconditioned data with Runge-Kutta integration and preconditioned data with artificial measurements extrapolated from the regression models.

In all cases the worst performance was realized with the center of gravity model using noisy data and Runge-Kutta integration. The use of preconditioned data with Runge-Kutta integration improved the performance of the center of gravity model by nearly 40% in some cases. The most notable improvement as found with the use of artificial measurements. The maximum prediction errors were reduced by 50% or more in each case. In every data set, the artificial measurements were a more effective means of improving the prediction performance of the center of gravity filter.

The prediction performance was also compared for the attitude/translation filters. The use of preconditioned measurements improved both the maximum and average prediction errors throughout the trajectory. The use of artificial measurements consistently showed decreased prediction errors over the use of Runge-Kutta integration. The use of vehicle specific inertia in the attitude/translation filter has a negligible effect on its predictive performance.

Overall, the use of attitude information has been confirmed as a means for improving tracking and predictive performance. Regression modelling in both preconditioning measurement data and extrapolating artificial measurements has been demonstrated to be a powerful tool for improving the performance of advanced tracking and prediction techniques.

Conclusions

A comparison of three different tracking and prediction filters was made based on a trajectory of actual aircraft performance data from an F-14A. A classic center of gravity tracker was compared to two attitude/translation tracking algorithms. One attitude/translation tracker used a white noise model for angular accelerations and the other considered vehicle specific inertia. The following results can be summarized from the performance tests:

1. Measuring and modelling the attitude of the aircraft produces a significant improvement in both tracking and prediction accuracy.

2. The use of vehicle specific inertia in an attitude/translation tracker has negligible effects on the improvement of tracking and prediction performance. Only limited aerodynamic and mass data are needed to achieve the performance improvements associated with trackers that include attitude information.

3. Preconditioning measurement data using adaptive regression modelling techniques has been shown to offer a substantial improvement in tracking and prediction performance. This approach requires no additional hardware in a real tracking environment and imposed limited computational overhead, yet is offers a significant enhancement in tracking and prediction performance.

4. Artificial measurements extrapolated from regression models of the measurement data offer a means of improving prediction accuracy over numerical integration of the state equations. This result suggests that regression modelling can capture the underlying dynamics of the measurements and infuse that additional information into the filter to improve predictive performance.

Recommendations

This study provide some evidence suggesting a number of ways of improving the tracking and prediction performance of advanced non-linear tracking filters. Since these approaches use extended Kalman filters, they are non-optimal in a theoretical sense. Therefore, there is a potential for performance improvement. The empirical evidence in this report does not offer proof of improved performance of trackers by using preconditioned data and artificial measurements. Rather, these results demonstrate the potential of these techniques. More investigation is warranted. The following studies are recommended:

1. Perform comparative studies of filter performance using other aircraft trajectories. A6 and AV8B data are immediately available for testing.

2. Perform comparative studies of filter performance using simulated trajectory data. This data is not subject to the limitations of actual radar data.

3. Use shorter range (and hence, more reliable) radar data in a suite of tests. Data should be used with ranges less than one mile to offer a comparison the extended range data used in this test.

Tables

Table 1. Symbols Used in the Tracker Models

L	Rolling Moment
M	Pitching Moment
N	Yawing Moment
I	Component of the Inertia Tensor
F	Force
ϕ	Roll Angle
θ	Pitch Angle
ψ	Yaw Angle
p	Roll Rate •
q	Pitch Rate •
r	Yaw Rate •
u	Forward Velocity •
v	Side Velocity •
w	Downward Velocity •
m	Vehicle Mass
k	Constant Dependent on Stability and Control Derivatives
α	Angle of Attack
β	Sideslip Angle
w	Process Noise
v	Measurement Noise
x,y,z	Cartesian Coordinates
x_i	State Variable (i = state index)
R	Range
η	Azimuth
ξ	Elevation
a	State Transition Function
h	Measurement Function
G	Process Noise Transformation Matrix
P	State Error Covariance
Q	Process Noise Covariance
R	Measurement Noise Covariance
τ	Correlation Time for Acceleration Model
T	Discrete Time Interval
b_j	Modelled Acceleration (j = x,y,z)
a_j	Acceleration (j = x,y,z)
v_j	Velocity (j = x,y,z)

• with respect to the earth coordinate system but transformed in vehicle coordinates

Table 2. Measurement Vector Used in the Tracker Models

$$z = \begin{bmatrix} \Phi \\ \theta \\ \Psi \\ R \\ \eta \\ \xi \\ \dot{R} \\ \dot{\eta} \\ \dot{\xi} \end{bmatrix} \begin{array}{l} \textit{ROLL} \\ \textit{PITCH} \\ \textit{YAW} \\ \textit{RANGE} \\ \textit{AZIMUTH} \\ \textit{ELEVATION} \\ \textit{RANGE RATE} \\ \textit{AZIMUTH RATE} \\ \textit{ELEVATION RATE} \end{array}$$

Table 3. State Equations for the Center of Gravity Tracker

$$\dot{b}_x = \frac{b_1}{\tau} + w_1$$

$$\dot{b}_y = \frac{b_y}{\tau} + w_2$$

$$\dot{b}_z = \frac{b_z}{\tau} + w_3$$

$$\dot{a}_x = 0$$

$$\dot{a}_y = 0$$

$$\dot{a}_z = 0$$

$$\dot{v}_x = a_x + (b_x + w_4)$$

$$\dot{v}_y = a_y + (b_y + w_5)$$

$$\dot{v}_z = a_z + (b_z + w_6)$$

$$\dot{x} = v_x + a_x T$$

$$\dot{y} = v_y + a_y T$$

$$\dot{z} = v_z + a_z T$$

Table 4. State Equations for the Attitude Translation Tracker

$$\dot{p} = [-(I_{zz} - I_{yy})qr + k_1\beta + k_2 p + k_3 r + k_4 w_1]/I_{xx}$$

$$\dot{q} = [-(I_{xx} - I_{zz})pr + k_7\alpha + k_8 q + k_9 w_2]\ /I_{yy}$$

$$\dot{r} = [-(I_{yy} - I_{xx})pq + k_{11}\beta + k_{12}p + k_{13}r + K_{15}w_3]/I_{zz}$$

$$\dot{\phi} = p + q\sin\phi\tan\theta + r\cos\phi\tan\theta$$

$$\dot{\theta} = q\cos\phi - r\sin\phi$$

$$\dot{\psi} = (q\sin\phi + r\cos\phi)\ /\ \cos\theta$$

$$\ddot{x} = [\cos\psi\sin\alpha\cos\theta - \cos\psi\cos\alpha\sin\theta\cos\phi - \sin\psi\cos\alpha\sin\phi]L/M + k_{16}(b_x + w_4)$$

$$\ddot{y} = [\sin\psi\sin\alpha\cos\theta - \sin\psi\cos\alpha\sin\theta\cos\phi + \cos\psi\sin\alpha\sin\phi]L/M + k_{16}(b_y + w_5)$$

$$\ddot{z} = [-\sin\alpha\sin\theta - \cos\alpha\cos\phi\cos\theta]L/M + g + k_{16}(b_z + w_6)$$

$$\dot{x} = \dot{x}$$

$$\dot{y} = \dot{y}$$

$$\dot{z} = \dot{z}$$

$$\dot{b}_x = \frac{b_x}{\tau} + w_7$$

$$\dot{b}_y = \frac{b_y}{\tau} + w_8$$

$$\dot{b}_z = \frac{b_z}{\tau} + w_9$$

Constants k_1-k_{15} are vehicle specific. These constants are set to zero and are compensated for by additive process noise.

Table 5. Measurement Noise

Measurement	Standard Deviation
ϕ	0.00076 rad
θ	0.00076 rad
ψ	0.00076 rad
R	2500 ft
η	0.000004 rad
ξ	0.000004 rad
$\dot{R}$	2500 ft/s
$\dot{\eta}$	0.000016 rad/s
$\dot{\xi}$	0.000016 rad/s

Figures

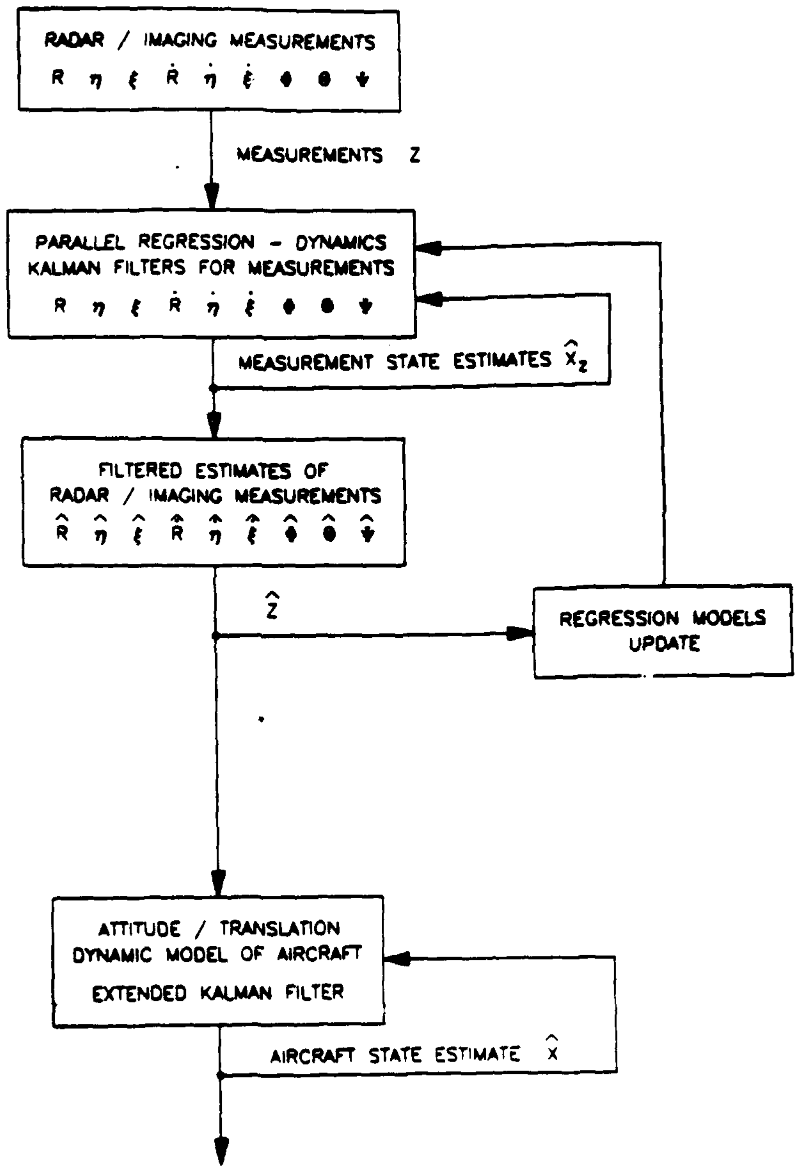

Figure 1 Schematic of Trajectory Estimation Technique Using Regression Models of Measurement Dynamics.

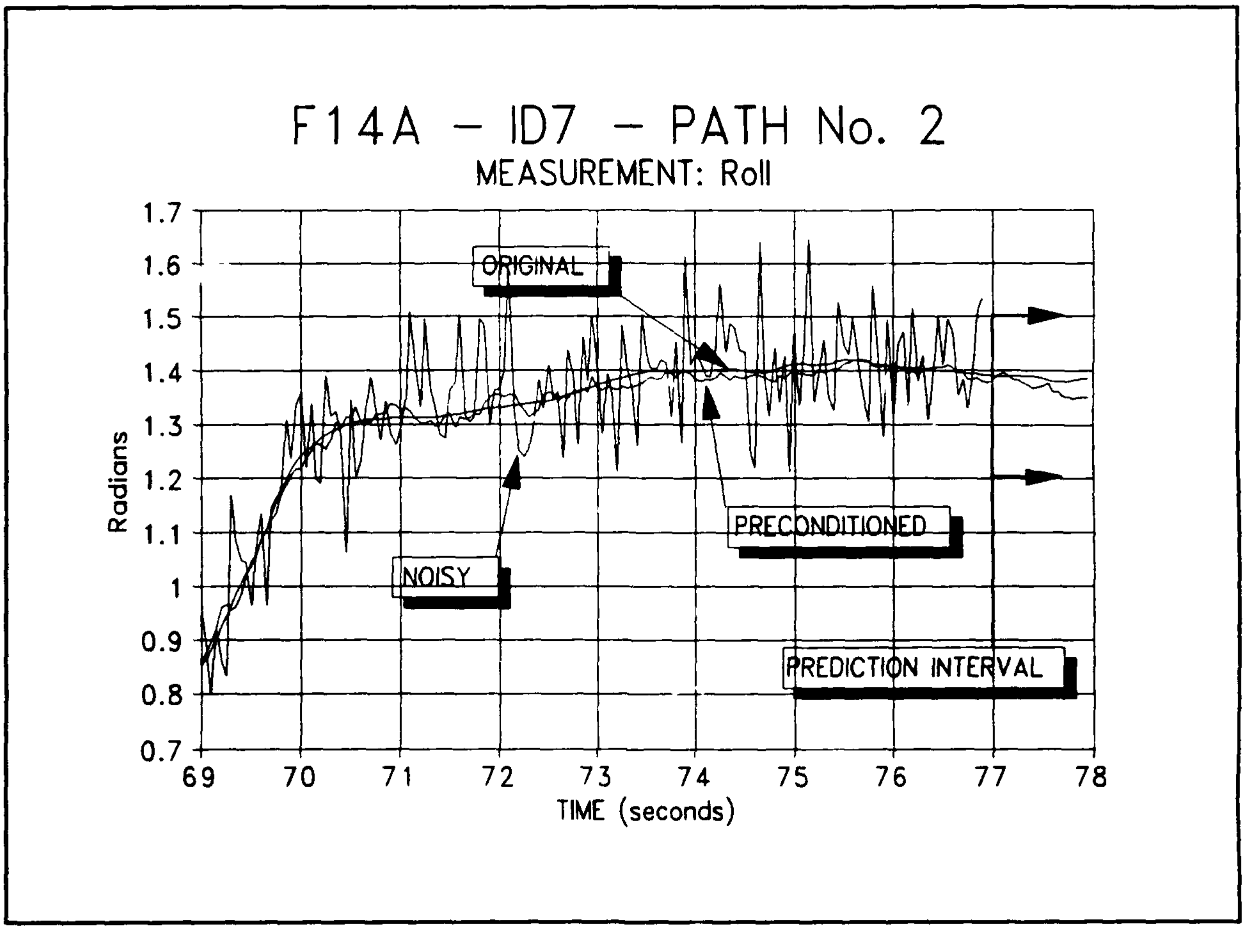

Figure 2 Trajectory Measurement Data: Roll

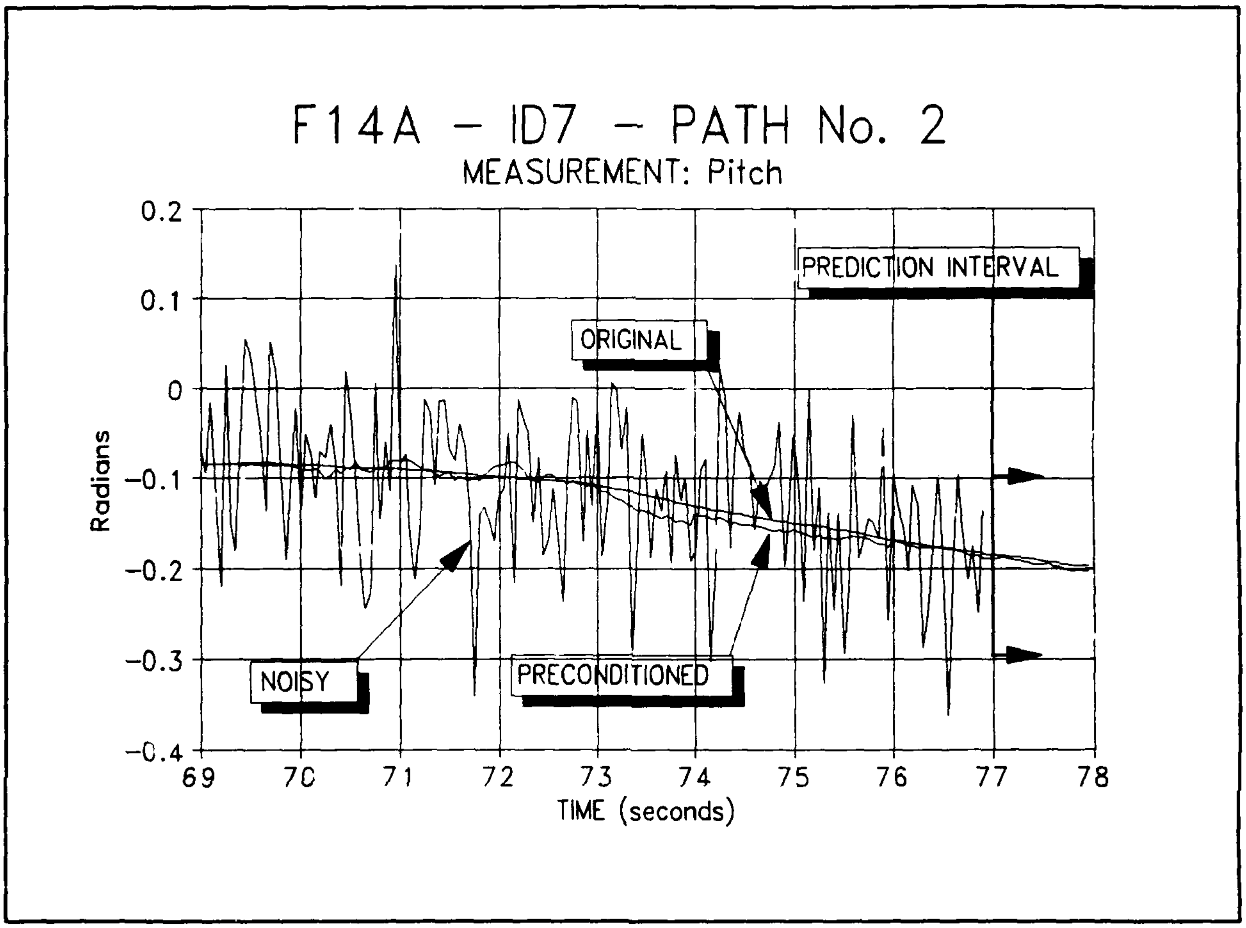

Figure 3 Trajectory Measurement Data: Pitch

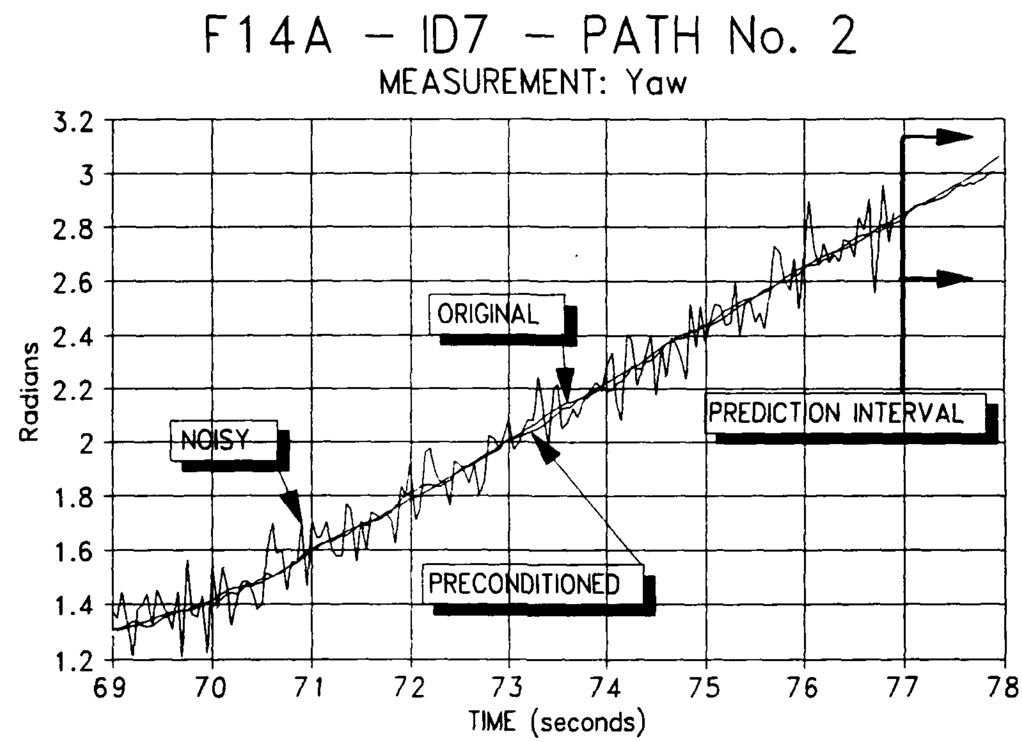

Figure 4 Trajectory Measurement Data: Yaw

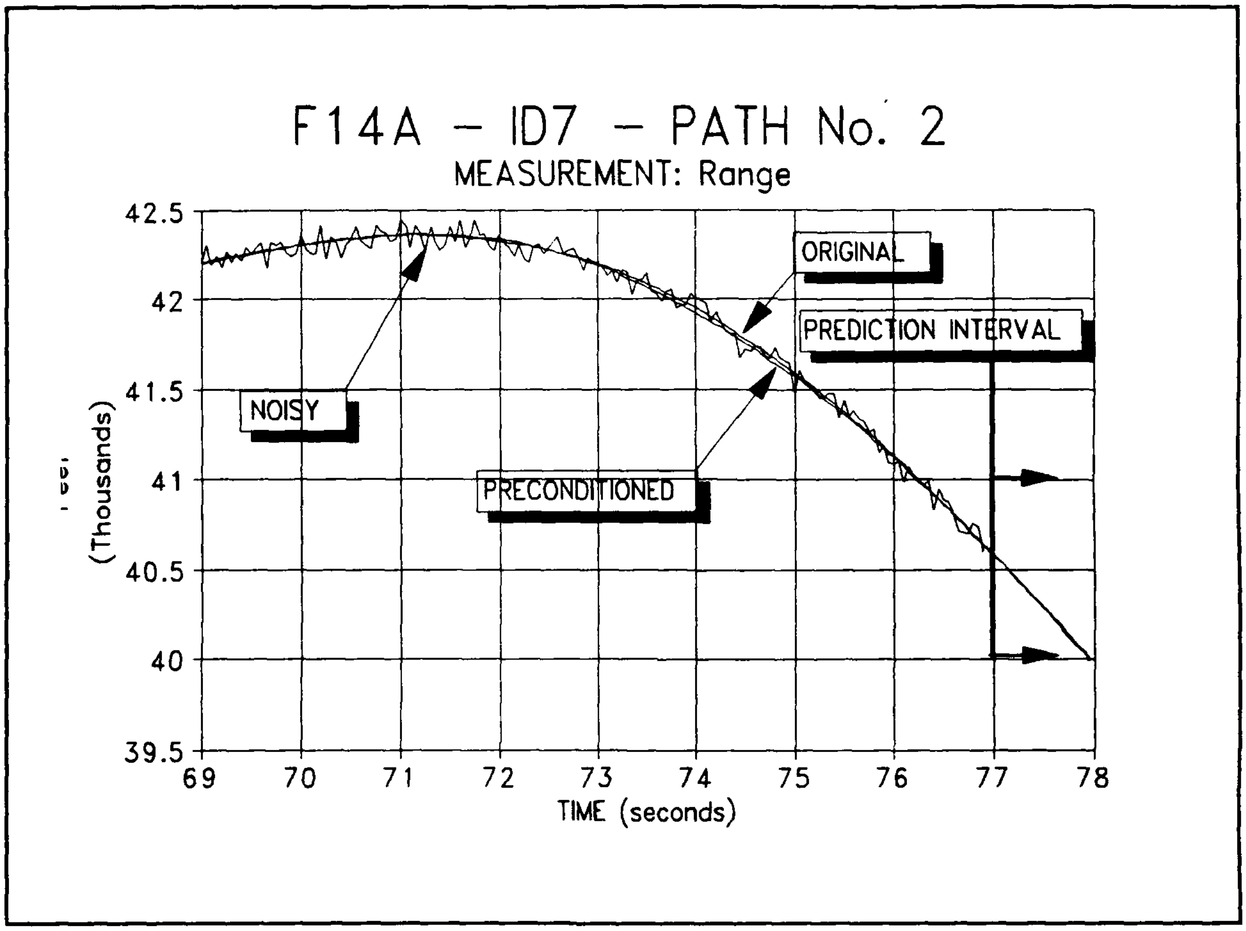

Figure 5 Trajectory Measurement Data: Range

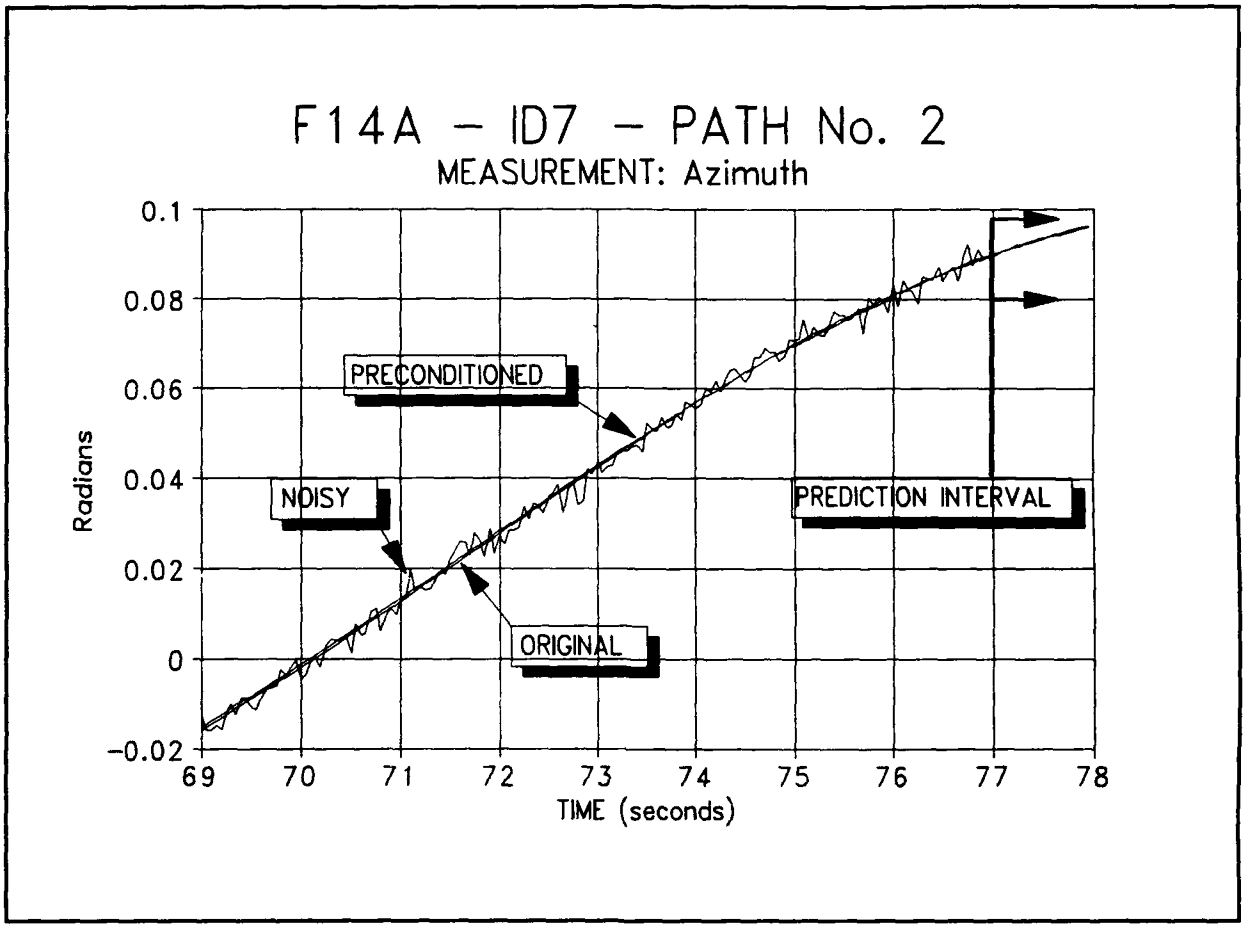

Figure 6 Trajectory Measurement Data: Azimuth

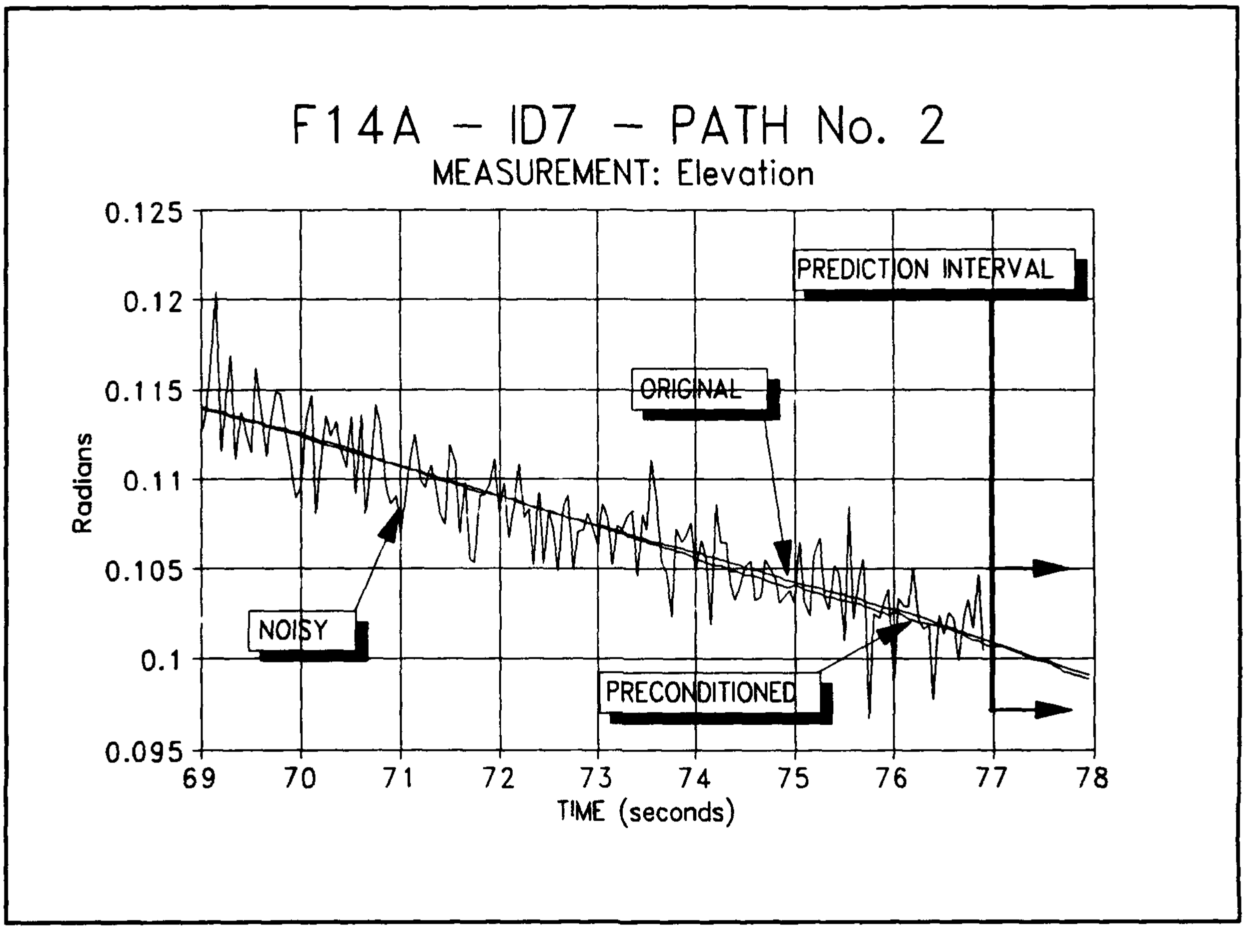

Figure 7 Trajectory Measurement Data: Elevation

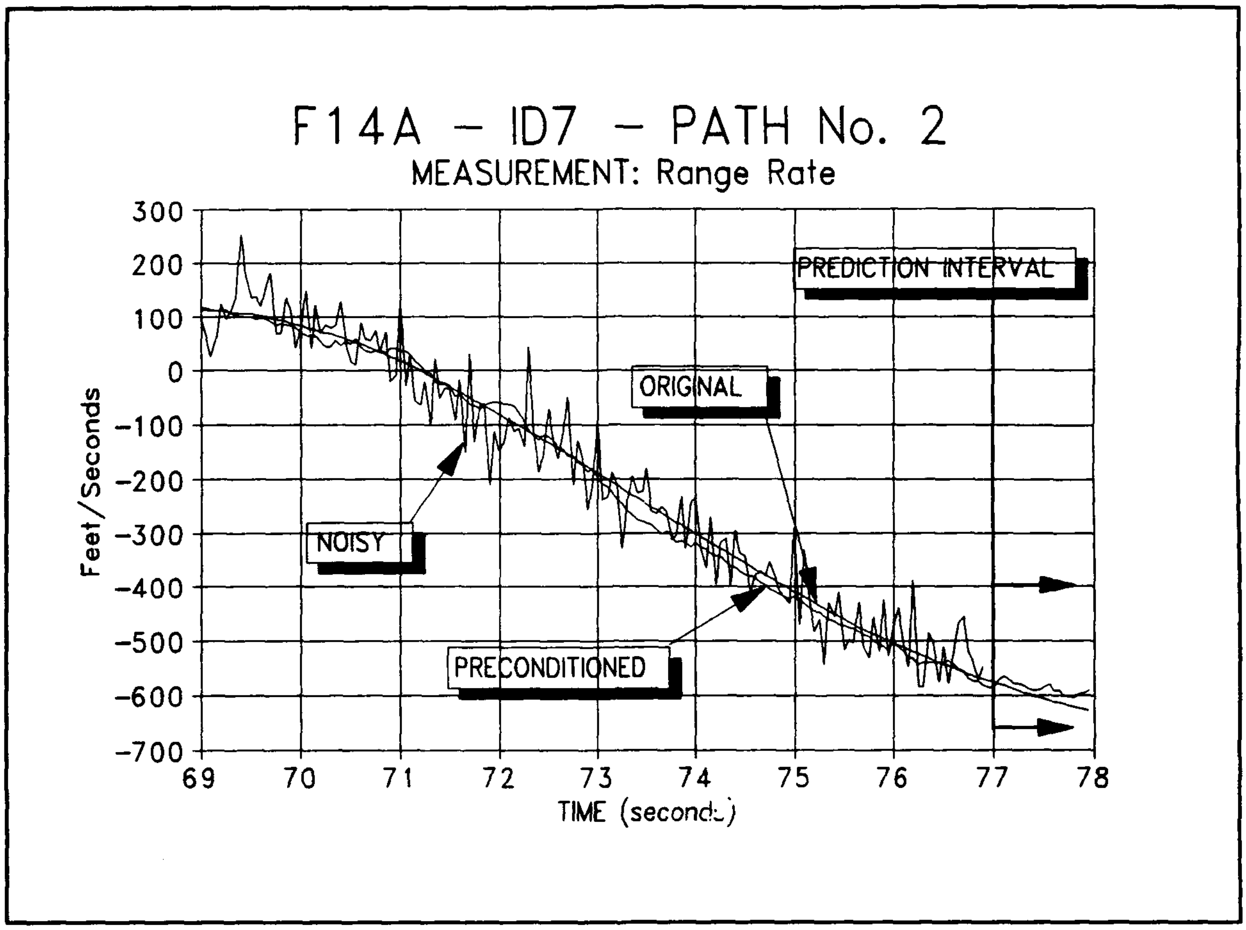

Figure 8 Trajectory Measurement Data: Range Rate

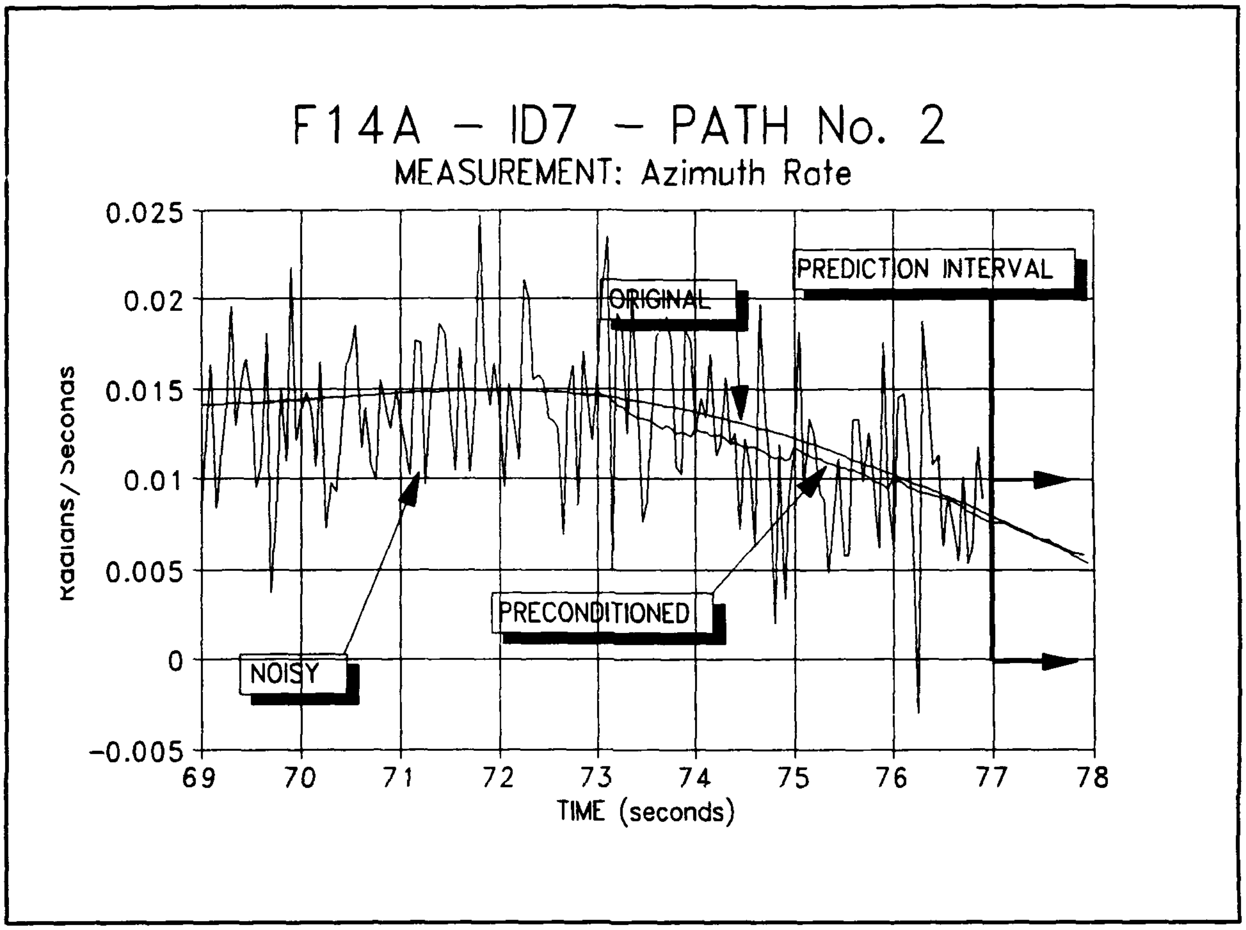

Figure 9 Trajectory Measurement Data: Azimuth Rate

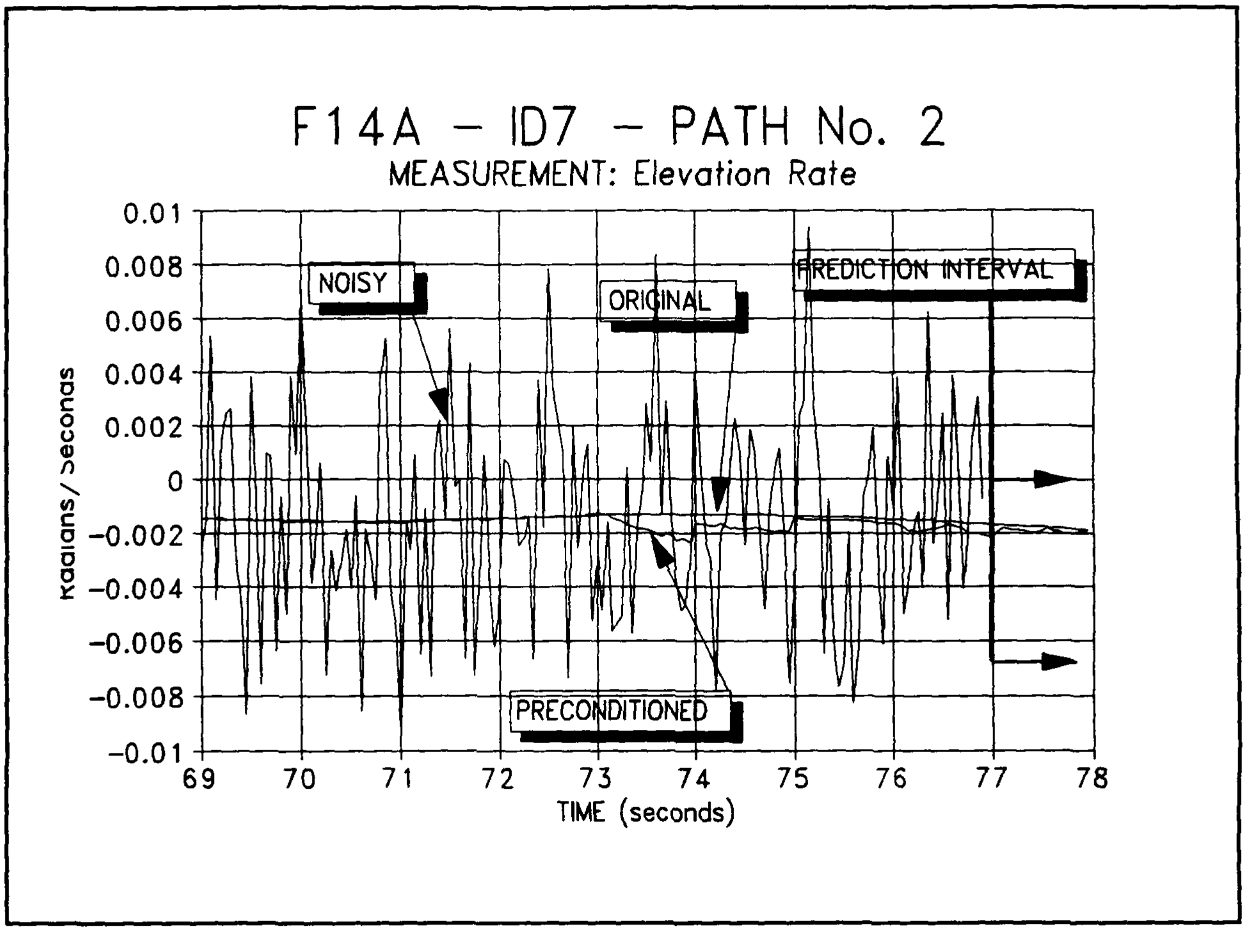

Figure 10 Trajectory Measurement Data: Elevation Rate

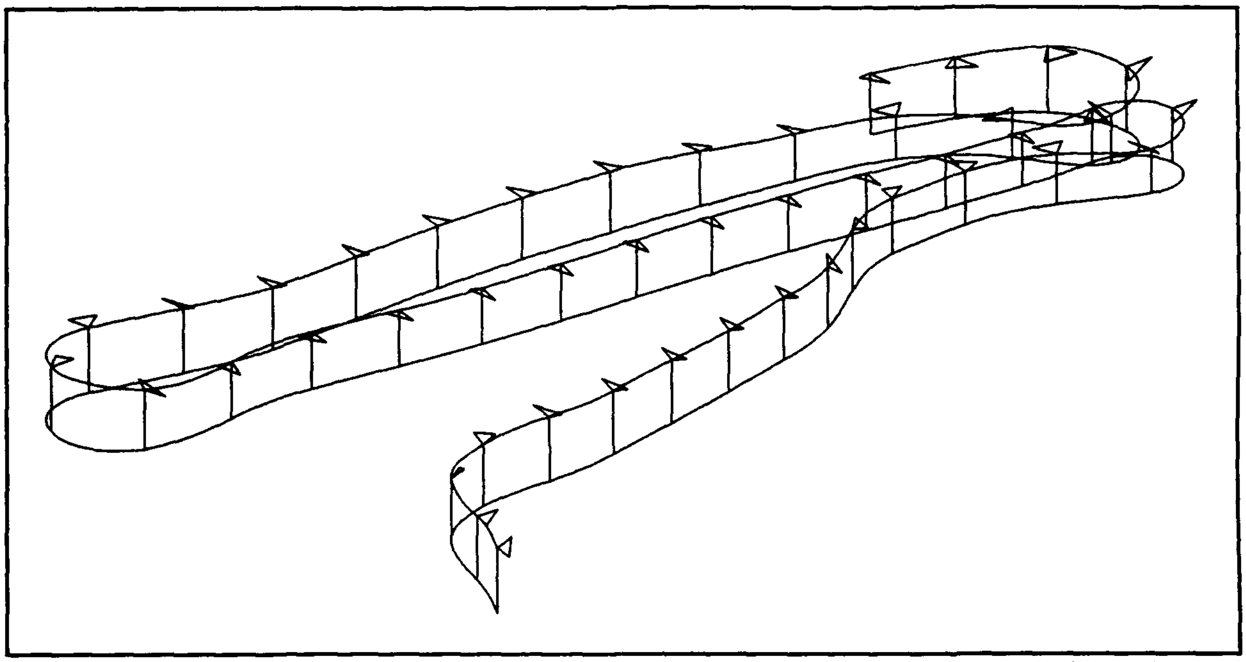

Figure 11 Complete F-14A Trajectory on TACTS Training Range (Cherry Point MCAS)

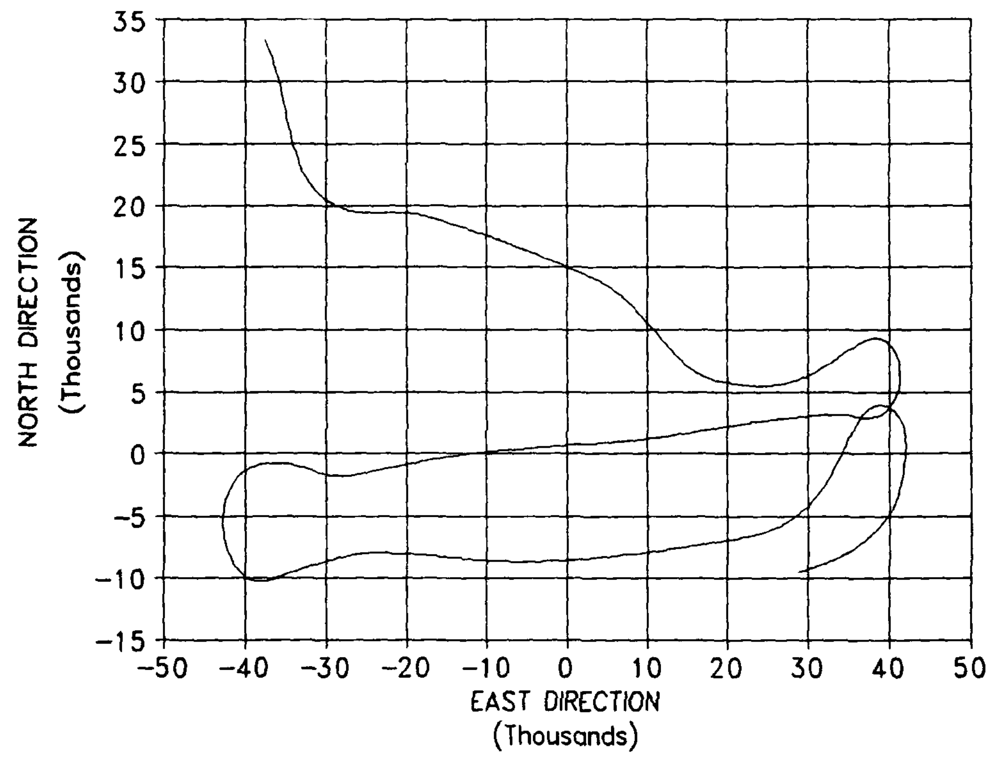

Figure 12 Plan View of Complete F-14A Trajectory

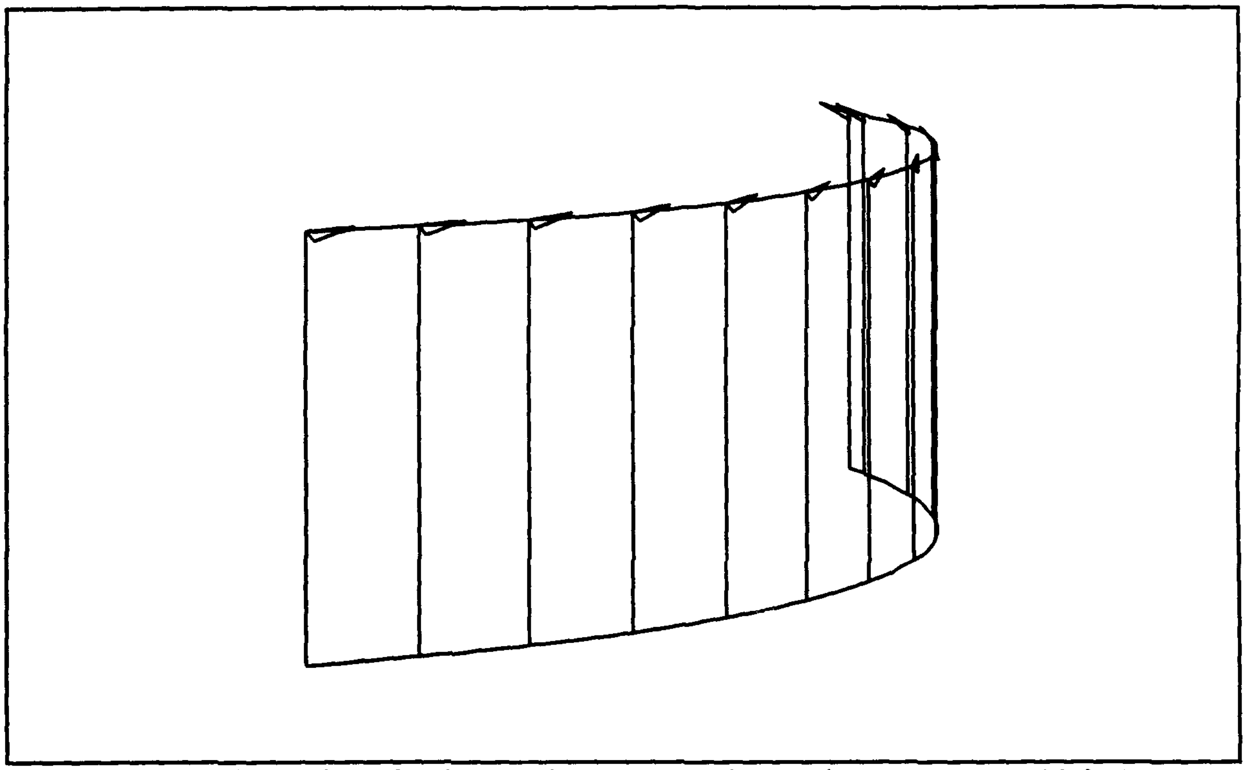

Figure 13 Portion of F-14A Trajectory Used for Testing (4g Turn and Dive)

Bibliography

1. Andrisani, D., F.P. Kuhl and D. Gleason, "A Nonlinear Tracker Using Attitude Measurements," IEEE Transactions on Aerospace and Electronic Systems, Vol. AES-22, No. 5, September 1986.

2. Andrisani, D., Gleason, D., and Kuhl, F.P, "A Tracker for Maneuvering Vehicles," Wescon/85, November 19-21, 1985, San Francisco, CA.

3. Andrisani, D., "Aircraft Trackers Using Attitude Measurements, Interim Report for the Period August 1985 - April 1986," School of Aeronautics and Astronautics, Purdue University, West Lafayette, IN, 1986.

4. Andrisani, D., "New Linear Tracking Filters," Proceedings of the 1985 American Control Conference, June 19-21 1985.

5. Andrisani, D., Kim, E.T., Schierman, J., and F.P. Kuhl, "A Nonlinear Helicopter Tracker Using Attitude Measurements," IEEE Transactions on Aerospace and Electronic Systems, Vol. AES-27, No. 1, January 1991.

6. Ashley, S., "Comanche: Tomorrow's High-Tech Helicopter," Mechanical Engineering, June 1991.

7. Bekey, G., and Karplus, W., Hybrid Computation, John Wiley and Sons, New York, 1968.

8. Berg, R.F., "Estimation and Prediction for Maneuvering Targets," IEEE Transactions on Automatic Control, AC-28.3, March 1983.

9. Bierman, G.J., Factorization Methods for Discrete Sequential Estimation, Academic Press, New York, 1977.

10. Blakelock, J.H., Automatic Control of Aircraft and Missiles, Second Edition, John Wiley & Sons, Inc., 1991.

11. Chang, C.B. and Tabaczynski J.A., "Application of State Estimation to Target Tracking," IEEE Transactions on Automatic Control, Vol. AC-29, No. 2, February 1984.

12. Chang, C.B., Whiting, R.H. and Athans, M., "On the State and Parameter Estimation for Maneuvering Reentry Vehicles," IEEE Transactions on Automatic control, Vol AC-22, February 1977.

13. Clark, B. L., "The Development of an Adaptive Kalman Target Tracking Filter," Proc. AIAA Guidance Control Conf., August 1976.

14. Craig, J., Introduction to Robotics: Mechanics and Control, Addison-Wesley Publishing Company, Inc., 1986.

15. DiFranco, J.V., Rubin, W.L., Radar Detection, Prentice-Hall, Inc., Englewood Cliffs, N.J., 1968.

16. Draper-Donley, M., Personal communication, Naval Air Systems Command (NAVAIR), Washington, March 1992.

17. Eagle, Paul and Tabrizi L.H., "State Model Estimation for Kalman Filter Application," Journal of Industrial Mathematics, (Accepted for Publication).

18. Eagle, Paul and Tabrizi L.H., "Regression Modelling Technique for State Model Estimation and Kalman Filter Application", Proceedings of the 1990 IEEE Conference on Systems, Man and Cybernetics, 1990.

19. Eagle, Paul and Tabrizi L.H., "State Model Estimation for Kalman Filter Applications Using Regression Techniques", Proceedings of the 29th IEEE Conference on Decision and Control, 1990.

20. Eagle, Paul and Tabrizi L.H., "Decision Theoretic Methods Applied to Fault Detection Using Features from State Models", Proceedings of the 1989 IEEE American Control Conference, 1989.

21. Eagle, Paul and Tabrizi L.H., "Application of Kalman Filters to Signature Monitoring Using Empirical Process Models", Proceedings of the Third International Conference on CAD/CAM and Robotics, 1988.

22. Finck, R.D., USAF Stability and Control Datcom, Flight Control Division, Air Force Flight Dynamics Laboratory, Wright-Patterson Air Force Base, Ohio, 1978.

23. Fitzgerald, R., "Simple Tracking Filters: Closed-Form Solutions", IEEE Transactions on Aerospace and Electronic Systems, Vol. AES-17, No. 6, November 1981.

24. Gelb, A., Applied Optimal Estimation, Cambridge, Mass., M.I.T. Press, 1974.

25. Gleason D. and Andrisani D., "Discrete Error Covariance Analysis for Tracking Filters," Proceedings of the Twenty First Annual Asilomar Conference on Signals Systems and Computers, pp. 344-350, November 2-4, 1987, Pacific Grove, CA.

26. Gleason D. and Andrisani D., "Error Covariance Analysis for Tracking Filters," Proceedings of the 1986 National Aerospace and Electronics Conference (NAECON), pp. 299-301, May 1986.

27. Lefas, C.C., "Using Roll-Angle Measurements to Track Aircraft Maneuvers," IEEE Transactions on Aerospace and Electronic Systems Vol. AES-20, No. 6, November 1984.

28. LeMay, J., Kalman Filtering: A National Short Course, Vol. I, St. Joseph Sciences, Inc., 1984.

29. Lewis, F., Optimal Estimation, John Wiley & Sons, New York, 1986.

30. Kendrick, J., "Estimation of Aircraft Target Motion Using Pattern Recognition Orientation Measurements," Ph.D. Dissertation, Air Force Institute of Technology, 1978.

31. Kendrick, J., Maybeck, P., Reid, J., "Estimation of Aircraft Target Motion Using Orientation Measurements," IEEE Transactions on Aerospace and Electronic Systems, Vol AES-17, No. 2, March 1981.

32. Pippett, B., Personal communication, TACTS Det., Loral Aerospace Services, November 1991.

33. Pippett, B., Personal communication, TACTS Det., Loral Aerospace Services, January 1992.

34. Pippett, B., Personal communication, TACTS Det., Loral Aerospace Services, February 1992.

35. Ridenour, L., Radar System Enginnering, McGraw-Hill Book Company, Inc., New York and London, 1947.

36. Roskman, J., "On Some Linear and Nonlinear Stability and Response Characteristics of Rigid Airplanes and a New Method to Integrate Nonlinear Ordinary Differential Equations," Ph.D. Dissertation, University of Washington, 1965.

37. Roskman, J., Airplane Flight Dynamics and Automatic Control, Part 1, Roskman Aviation and Engineering Corp., The University of Kansas, Lawrence, K.S., 1979.

38. Roskman, J., Airplane Flight Dynamics and Automatic Control, Part 2, Roskman Aviation and Engineering Corp., The University of Kansas, Lawrence, K.S.,

1979.

39. Seckel, E., Stability and Control of Airplanes and Helicopters, Academic Press, New York, 1964.

40. Singer, R., "Estimating Optimal Tracking Filter performance for Manned Maneuvering Targets," IEEE Transactions on Aerospace and Electronic Systems, Vol. AES-6, No. 4, July 1970.

41. Sklansky, J., Davison, G., "Recognizing Three-Dimensional Objects By Their Silhouttes," AGARD Conf. Proc., (No. 94 on Artificial Intelligence), May 1971.

42. Skolnik, M. I., Introduction to Radar Systems, Second Edition, McGraw-Hill Book Company, 1980.

43. Stevens, L.B., Lewis, F.L., Aircraft Control and Simulation, John Wiley & Sons, Inc., 1992.

44. Wrigley, W., Hovorka, J., Fire Control Principles, First Edition, McGraw-Hill Book Company, 1959.

45. Young, T.Y., and Calvert, T.W., Classification Estimation, and Pattern Recognition, New York, Elsevier Publishing Co., 1974.

46. ----, Principles of Radar, Second Edition, McGraw-Hill Book Company, Inc., New York and London, 1946.

APPENDIX A

CONVERSION OF A POWER SERIES REGRESSION EQUATION INTO A DISCRETE TIME STATE MODEL

This work uses a novel approach to convert power series, time-based, regression models into discrete state models. A power series regression model of discrete time steps:

$$y(kT) = b_0(kT)^0+b_1(kT)^1+b_2(kT)^2+ \cdots +b_n(kT)^n+e(kT)$$

is used to represent dynamics in the form of the conventional time derivative of the continuous-time regression equation:

$$\frac{dy(t)}{dt} = b_1+2b_2t+ \cdots nb_nt^{n-1}+\frac{de(t)}{dt}$$

The state equations can be placed in matrix format as:

$$\boldsymbol{x}(k+1) = \boldsymbol{A}\boldsymbol{x}(k)+\boldsymbol{B}\boldsymbol{u}(k)$$

In this technique, the A matrix for this system can be generalized as a constant matrix:

$$\boldsymbol{A} = \begin{bmatrix} A_1 & | & A_2 \\ - & - & - \\ & A_3 & \end{bmatrix}_{nxn}$$

where

$$A_1 = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix}_{n-1x1}$$

$$A_2 = [I]_{n-1xn-1}$$

and

$$A_3 = \left[(-1)^{n+1}\binom{n}{n} \; (-1)^n\binom{n}{n-1} \; \cdots \; (-1)^{n-j+2}\binom{n}{n-j+1} \; (-1)^2\binom{n}{1}\right]_{1xn}$$

The **B** matrix takes the form of a constant matrix:

$$B = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \\ 1 \end{bmatrix}_{n \times 1}$$

The output equation of the system, representing the measurement data, is given as:

$$y(k) = \sum_{i=1}^{n} \left((-1)^{n-i} \binom{n}{n-i+1} \alpha_0 + \alpha_{n-i+1} \right) x_i(k) + \alpha_0 u(k) + e(k)$$

$$\alpha_i = \begin{cases} (-1)^i \sum_{j=1}^{n-i} j! \binom{n-j}{i} b_j T^j & , \ 0 \le i < n-1 \\ 0 & , \ \textit{elsewhere} \end{cases}$$

In matrix format, this can be given as:

$$y(k) = Cx(k) + Du(k) + e(k)$$

where **C** can be defined as:

$$C = \Big[(-1)^{n-1} \binom{n}{n} \alpha_0 + \alpha_n \quad (-1)^{n-2} \binom{n}{n-1} \alpha_0 + \alpha_{n-1} \quad \cdots$$
$$(-1)^{1} \binom{n}{2} \alpha_0 + \alpha_2 \quad (-1)^{0} \binom{n}{1} \alpha_0 + \alpha_1 \Big]_{1 \times n}$$

and **D** is defined as the constant matrix:

$$\boldsymbol{D} = [\alpha_0]_{1 \times 1}$$

The result is a state model of a power-series regression estimate, supplying the necessary data for implementation of the Kalman Filter.

APPENDIX B

COMPARISONS OF TRACKING AND PREDICTION PERFORMANCE

Table B1

Tracking Errors - Interval: 69-74 Seconds							
Input Data	Tracker Type	Error Measurement (Feet)					
		X Max	Y Max	Z Max	Max	Average	RMS
Noisy	CG	22.94	79.70	83.20	116.87	40.2	50.67
	AT	31.84	42.19	72.68	85.01	30.22	35.77
	AT-VSI	31.84	43.14	72.65	84.98	30.22	36.76
Preconditioned	CG	29.09	28.73	15.61	35.52	24.88	35.76
	AT	29.21	30.69	16.74	35.85	26.25	25.23
	AT-VSI	29.21	30.69	16.74	35.85	26.25	26.52

Prediction Error - Tracking Interval: 69-74 Seconds Prediction Interval: 74 - 75 Seconds							
Input Data/ Prediction Method	Tracker Type	Error Measurement (Feet)					
		X Max	Y Max	Z Max	Max	Average	RMS
Noisy/ Runge Kutta	CG	25.71	135.15	162.35	212.60	164.65	167.17
	AT	28.07	43.96	139.14	142.78	112.70	113.93
	AT-VSI	28.06	15.31	138.81	142.22	112.54	113.75
Preconditioned/ Runge Kutta	CG	50.48	75.98	61.30	109.91	70.75	74.16
	AT	36.41	71.19	60.94	99.93	67.48	70.09
	AT-VSI	36.42	71.17	60.86	99.86	67.45	70.06
Preconditioned/ Artificial Measurements	CG	31.76	46.76	34.07	63.65	45.95	46.64
	AT	31.99	37.62	28.36	54.37	41.81	42.19
	AT-VSI	31.99	37.62	28.36	54.37	41.81	42.19

Table B2

Tracking Errors - Interval: 69-75 Seconds							
Input Data	Tracker Type	Error Measurement (Feet)					
		X Max	Y Max	Z Max	Max	Average	RMS
Noisy	CG	21.50	88.42	89.14	125.95	49.83	60.68
	AT	16.55	51.46	85.06	98.64	36.78	46.16
	AT-VSI	16.55	51.47	84.98	98.59	36.76	46.13
Preconditioned	CG	21.10	40.61	22.06	48.75	26.75	27.56
	AT	20.94	33.13	21.77	42.79	27.33	27.81
	AT-VSI	20.94	33.13	21.77	42.79	27.33	27.81

Prediction Error - Tracking Interval: 69-75 Seconds Prediction Interval: 75 - 76 Seconds							
Input Data/ Prediction Method	Tracker Type	Error Measurement (Feet)					
		X Max	Y Max	Z Max	Max	Average	RMS
Noisy/ Runge Kutta	CG	7.33	70.30	34.78	75.66	36.85	40.77
	AT	50.74	70.70	96.61	130.03	89.6	91.42
	AT-VSI	50.71	70.80	96.5	129.64	88.91	91.15
Preconditioned/ Runge Kutta	CG	14.63	65.18	37.88	75.82	64.95	63.38
	AT	15.40	61.90	41.04	74.68	61.49	62.12
	AT-VSI	15.40	61.87	40.93	74.59	61.46	62.9
Preconditioned/ Artificial Measurements	CG	15.11	42.13	28.55	50.99	47.61	47.77
	AT	15.69	33.46	26.65	43.64	38.80	39.11
	AT-VSI	15.69	33.46	26.65	43.64	38.80	39.11

Table B3

Tracking Errors - Interval: 69-76 Seconds							
Input Data	Tracker Type	Error Measurement (Feet)					
		X Max	Y Max	Z Max	Max	Average	RMS
Noisy	CG	29.60	88.15	90.68	128.50	52.51	63.41
	AT	31.84	51.26	86.14	100.24	43.36	51.33
	AT-VSI	31.84	51.26	86.08	100.19	43.33	51.29
Preconditioned	CG	34.85	44.85	23.97	59.14	32.38	34.89
	AT	34.71	37.63	23.59	53.82	32.15	33.75
	AT-VSI	34.71	37.63	23.59	53.82	32.15	33.75

Prediction Error - Tracking Interval: 69-76 Seconds Prediction Interval: 76 - 77 Seconds							
Input Data/ Prediction Method	Tracker Type	Error Measurement (Feet)					
		X Max	Y Max	Z Max	Max	Average	RMS
Noisy/ Runge Kutta	CG	40.73	57.25	87.61	108.53	95.82	96.14
	AT	18.39	90.36	95.92	132.55	93.02	94.68
	AT-VSI	18.40	90.51	95.06	132.04	92.65	94.30
Preconditioned/ Runge Kutta	CG	26.57	57.04	19.94	63.73	59.65	59.69
	AT	35.31	62.35	19.31	72.53	63.32	63.73
	AT-VSI	35.33	62.32	19.31	72.49	63.30	63.71
Preconditioned/ Artificial Measurements	CG	26.49	60.99	20.91	65.29	60.73	60.79
	AT	25.70	54.00	19.82	58.45	54.19	54.26
	AT-VSI	25.70	54.00	19.82	58.45	54.19	54.26

Table B4

Tracking Errors - Interval: 69-77 Seconds							
Input Data	Tracker Type	Error Measurement (Feet)					
		X Max	Y Max	Z Max	Max	Average	RMS
Noisy	CG	16.42	56.66	69.26	78.42	31.24	34.59
	AT	25.95	45.47	70.36	71.06	35.35	37.72
	AT-VSI	25.95	45.46	70.36	71.06	35.35	37.24
Preconditioned	CG	34.86	44.69	23.97	59.14	33.59	35.92
	AT	34.71	37.46	23.59	53.87	32.43	33.91
	AT-VSI	34.71	37.46	23.59	53.82	32.43	33.91

Prediction Error - Tracking Interval: 69-77 Seconds Prediction Interval: 77 - 78 Seconds							
Input Data/ Prediction Method	Tracker Type	Error Measurement (Feet)					
		X Max	Y Max	Z Max	Max	Average	RMS
Noisy/ Runge Kutta	CG	12.09	121.82	48.49	131.20	100.80	102.63
	AT	15.66	67.61	22.33	70.12	41.11	43.43
	AT-VSI	15.65	67.75	22.82	70.47	41.38	43.71
Preconditioned/ Runge Kutta	CG	17.91	26.43	29.23	38.79	32.96	33.11
	AT	26.91	24.17	32.46	46.42	33.72	34.48
	AT-VSI	26.96	24.16	32.29	46.31	33.68	34.44
Preconditioned/ Artificial Measurements	CG	10.79	24.16	11.80	28.98	22.39	22.54
	AT	10.34	17.08	10.06	22.36	16.84	16.96
	AT-VSI	10.34	17.08	10.06	22.36	16.84	16.96

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